PRDP:
Progressively Refined Differentiable Physics

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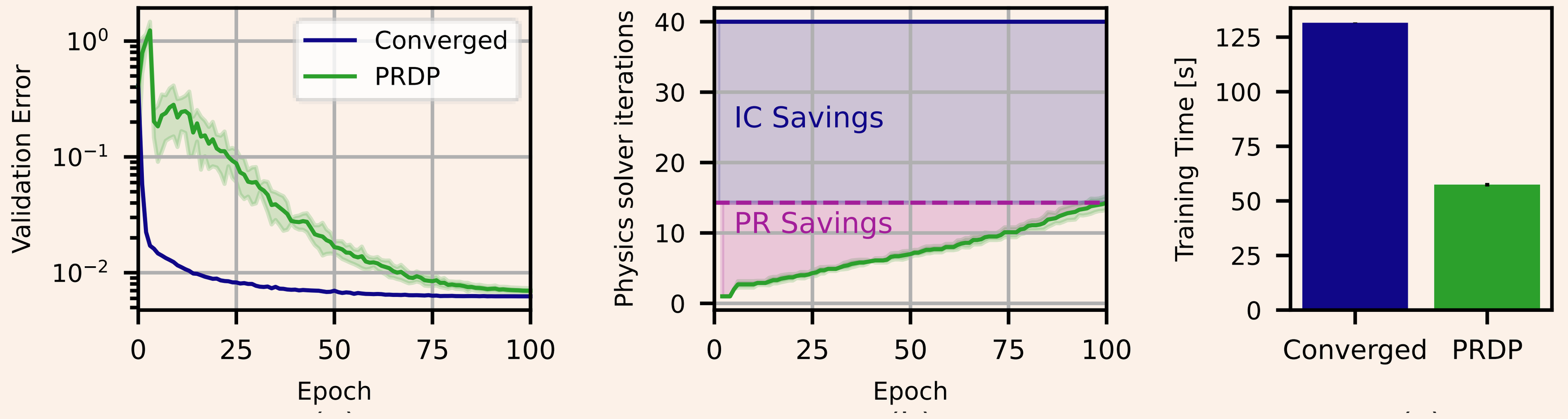
Key Results

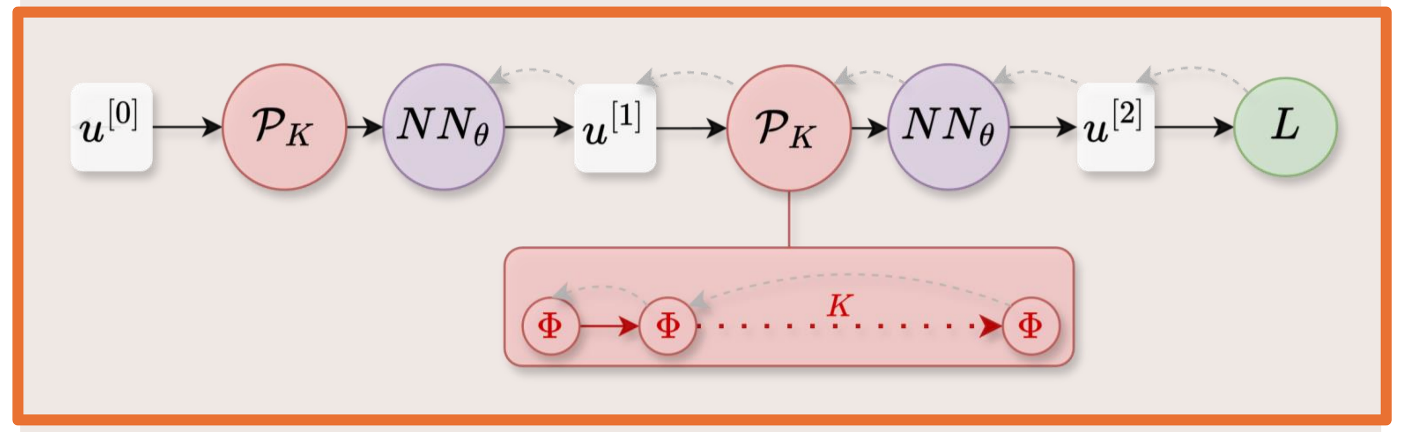


PRDP saves training time by up to 78% without sacrificing network performance.

Motivation

- Differentiable Physics = physics solvers written in a differentiable framework e.g. JAX.
- Enable neural networks to interact with physics during training, allowing neural networks to generalize better [1,2].

However, gradients of physics solvers are expensive due to iterations in each forward as well as backward pass.

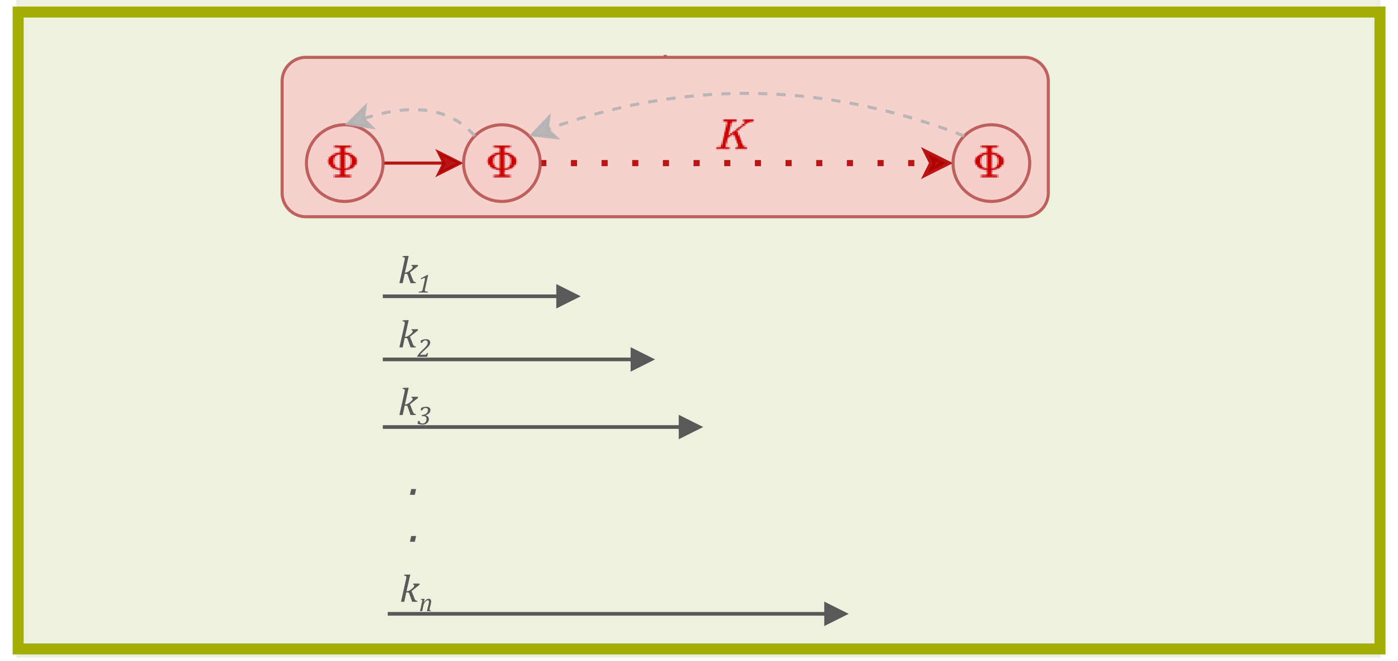


✅ Our method accelerates training by using fast approximates of the physics and its gradient.

The PRDP Idea

- Begin training with coarse physics,
- adaptively refine it during training, and
- stop refinement before full numerical convergence.

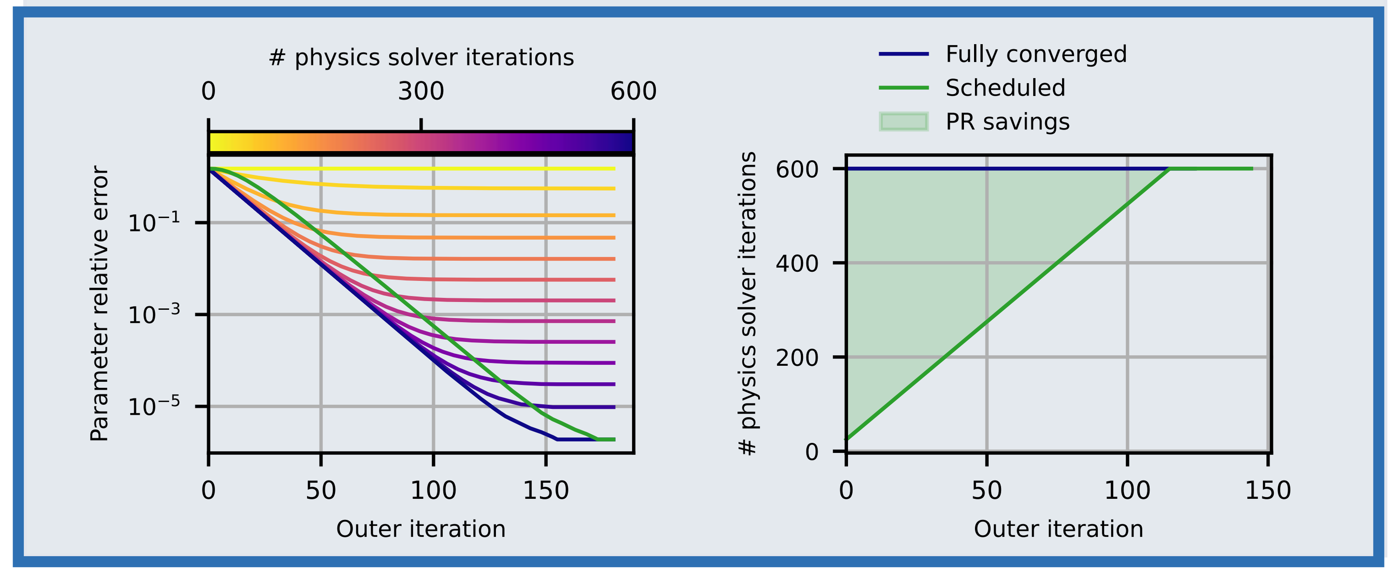
✅ Uses fewer cumulative solver iterations without sacrificing network training performance.



Idea 1: Progressive Refinement (PR) of Physics

Training through coarse physics (yellow) may yield lower training performance than fully converged physics (blue).

✅ Progressive physics refinement - initial estimates are made cheap, while later training benefits from refined physics. [3]

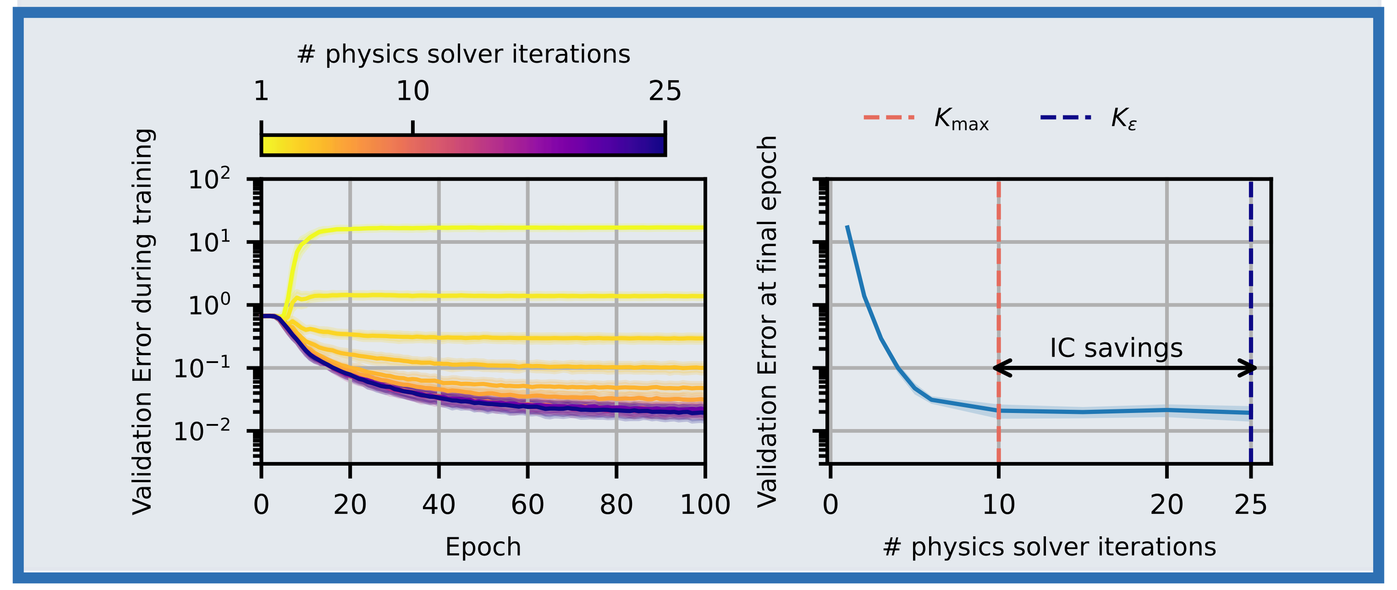


Idea 2: Incomplete Convergence (IC) of Physics

Traditionally, physics solver iterations run until numerical convergence.

However, full solver convergence is often unnecessary - training is effective even when the physics is incompletely converged (IC).

✅ IC physics saves significant compute in each epoch.

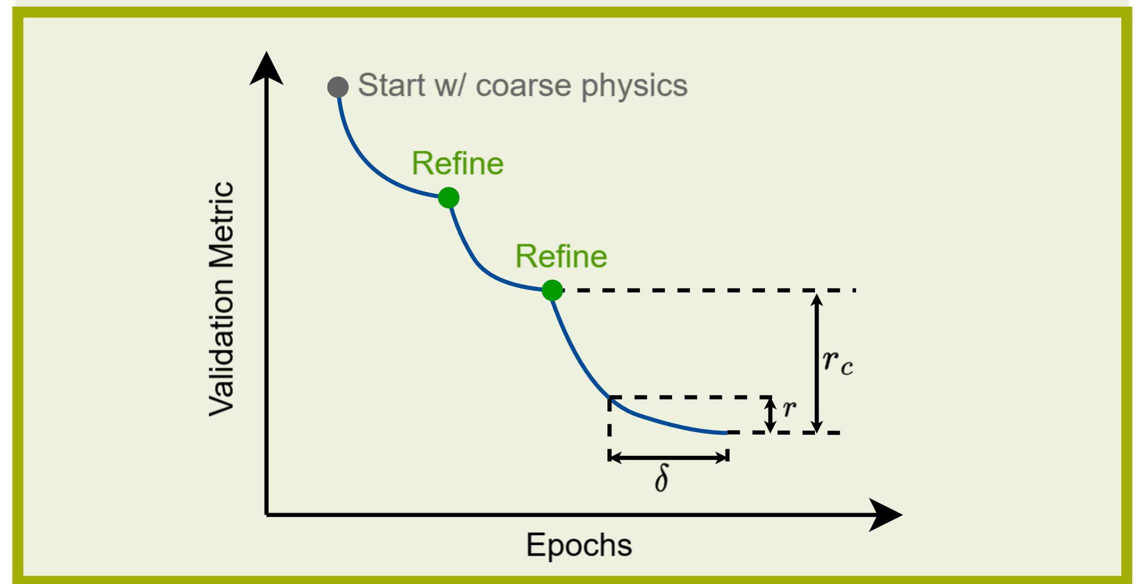


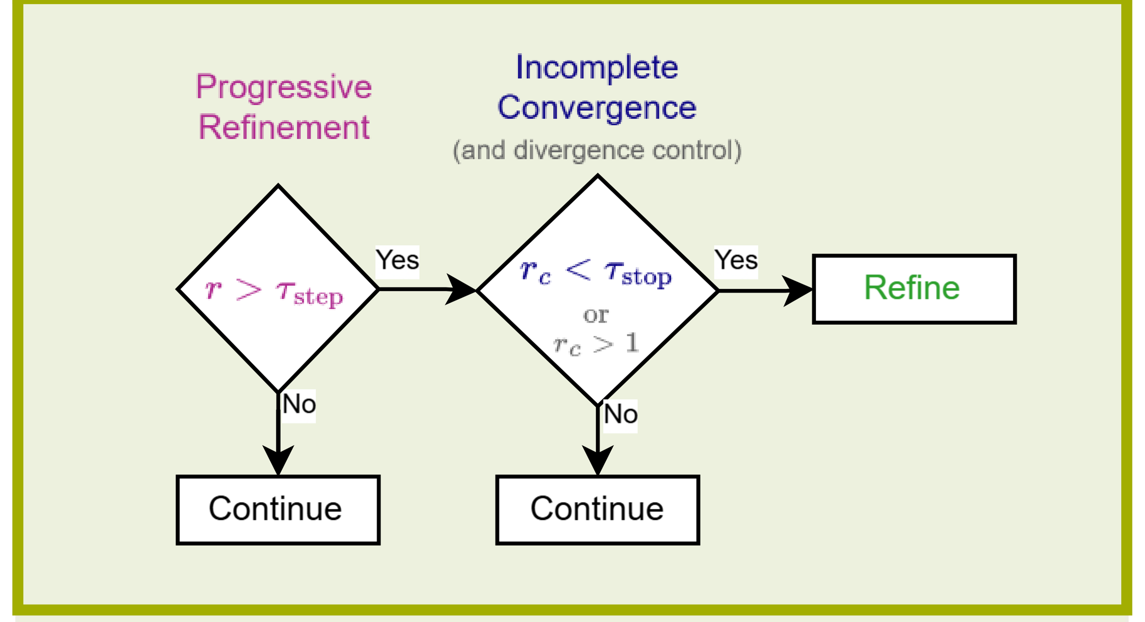
The PRDP Algorithm

A suitable refinement schedule for PR and level of refinement for IC are:

- problem dependent, and
- unknown apriori.

✅ The PRDP algorithm adaptively performs PR and IC by measuring plateaus in training progress.



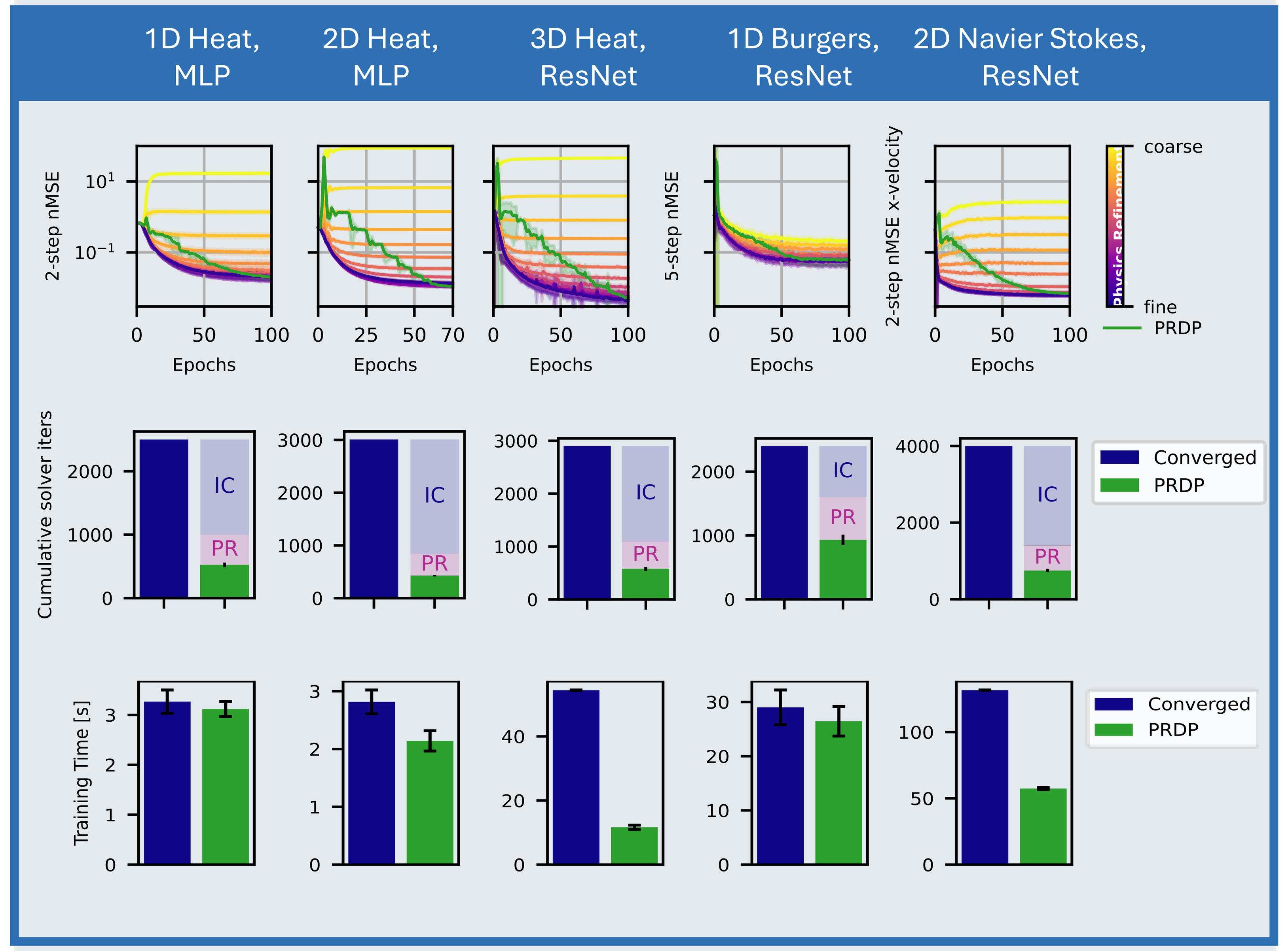


Controllable Parameters for Fine Tuning:

- τ_{step}: how aggressive is the progressive refinement.
- τ_{stop}: how aggressively the refinement is stopped towards the end of training.
- δ: lookback period (epochs).

Results

In neural emulator training tasks for a variety of PDEs, PRDP reduces the cumulative number of physics solver iterations by 59 to 86 %.
In the 3D Heat Equation case, this corresponds to a 78% savings in wall clock time.



💡 PRDP is most effective in training pipelines where the physics solver is the bottleneck, e.g. in three-dimensional or ill-conditioned physics.

Summary of Contributions

1. We empirically demonstrate that full network performance can be achieved with a coarse level of physics refinement, well below the typical refinement required for full convergence, leading to significant computational savings.
2. We introduce the Progressively Refined Differentiable Physics (PRDP) algorithm, which adaptively identifies the optimal level of physics refinement during training.
3. We validate the effectiveness of PRDP across various differentiable physics learning scenarios, demonstrating its broad applicability.

References

[1] Um et. al. (2019), Solver-in-the-loop.
[2] Kochkov et. al. (2021), Machine learning accelerated computational fluid dynamics.
[3] Pedregosa et. al. (2016), Hyperparameter optimization with approximate gradient.